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Characterization of Households and its Implications for the Vegetation of Urban Ecosystems

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Abstract

Our understanding of the dynamics of urban ecosystems can be enhanced by examining the multidimensional social characteristics of households. To this end, we investigated the relative significance of three social theories of household structure—population, lifestyle behavior, and social stratification—to the distribution of vegetation cover in Baltimore, Maryland, USA. Our ability to assess the relative significance of these theories depended on fine-scale social and biophysical data. We distinguished among vegetation in three areas hypothesized to be differentially linked to these social theories: riparian areas, private lands, and public rights-of-way (PROWs). Using a multimodel inferential approach, we found that variation of vegetation cover in riparian areas was not explained by any of the three theories and that lifestyle behavior was the best predictor of vegetation cover on private lands. Surprisingly, lifestyle behavior was also the best predictor of vegetation cover in PROWs. The inclusion of a quadratic term for housing age significantly improved the models. Based on these research results, we question the exclusive use of income and education as the standard variables to explain variations in vegetation cover in urban ecological systems. We further suggest that the management of urban vegetation can be improved by developing environmental marketing strategies that address the underlying household motivations for and participation in local land management.

Key words: urban ecology; population; household; social stratification; lifestyle behavior; vegetation; Baltimore; long term ecological research (LTER).

Introduction

Recent ecological studies have highlighted the importance of households and their behavior to the biophysical environment. Liu and others (2003) and Keilman (2003) found that the number of households increases much faster than the total population, and this rapid increase has important implications for biodiversity and the consumption of natural resources. Oldfield and others (2003) noted a relationship between household participation in outdoor recreation and household land management practices. Implied by these ecological results is the question of whether households are generic and unidimensional in the ecological roles they play, or whether they differ along various dimensions that affect their ecological behaviors. Although the shift in emphasis from total population size to households as a unit of analysis is

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significant and positive, we propose that a multidimensional characterization of households would enable a more complete understanding of the motivations, pathways, impacts, and responses of households to ecological change.

Extensive social science research on household behavior clearly indicates that households are multidimensional. For instance, households have been characterized in terms of social class and lifestyle (Blumin 1989; Higley 1995), reference groups (Merton and Kitt 1950; Shibutani 1955; Singer 1981), and consumer activity (Veblen 1981 [1899]; Horowitz 1985; Schor and Holt 2000; Matt 2003). These characteristics may explain variations among households in the types of employment households seek, what they choose to buy, where they choose to live, how they organize through participation in formal and informal associations, and how they spend their leisure time.

Burch and DeLuca (1984) have shown how household characteristics such as housing and settlement preferences, household size and life stage, cultural traditions, access to power and knowledge, and group identity and status can influence social and biophysical structures and functions. These interactions can be described and examined in a human ecosystem context (for example, Machlis and others 1997; Redman and others 2004). As human ecosystem research is applied to urban areas, there is a growing need to answer the question of whether the usual suspects—population density, income and education, and ethnicity (Whitney and Adams 1980; Palmer 1984; Grove and Burch 1997; Dow 2000; Vogt and others 2002; Hope and others 2003)—are adequate as explanatory social variables (Grove and others 2005).

This question is particularly relevant in light of a growing recognition among researchers and managers that there is a wide diversity in the targets, goals, and agents of management (Svendsen 2005). For example, the set of targets for urban forestry management includes such areas as stream valleys, large protected parks, abandoned industrial areas, neighborhoods, and public rights-of-way (PROWs). The set of management agents is also broad and is characterized by varying motivations and capacities; this set includes local and state agencies, nonprofit organizations, businesses, and homeowners (Grove and others 2005). Government agencies and environmental nonprofit organizations increasingly seek to understand the links between the distribution of woody and grass vegetation associated with various urban forestry types and different scales of management. In this context, more attention is being paid to the questions of why and how landowners do what they do on their property and in their neighborhood (Burch and Grove 1993; Vogt and others 2002; Grove and others 2005).

Urban vegetation performs a variety of important ecosystem functions. Amelioration of urban microclimates, particularly temperature extremes, and the modification of atmospheric humidity result from vegetation cover. Similarly, albedo and radiation loads can be reduced by vegetation (Sukopp and Werner 1982; Oke 1990). Woody plants of appropriate height and location can reduce heating and air conditioning requirements through their radiative properties and ability to slow winds (Nowak 1994a). Vegetation can absorb particulate pollution from the atmosphere and reduce nonpoint water pollution (Randolph 2004). It can stabilize stream sides, mitigate storm water flow and improve its quality, and convert nitrate pollution to harmless gaseous nitrogen. Vegetated surfaces can contribute to the perviousness of urban areas and enhance the recharge of water tables. Plants in urban environments may contribute to carbon sequestration and hence play an underappreciated role in global carbon budgets (Nowak 1994b; Jenkins and Riemann 2003). Vegetation also provides habitat for animals in metropolitan settings (Breuste and others 1998).

To begin to understand the link between urban vegetation cover and different levels of management, we examined the distribution of grass and tree cover in residential areas on the basis of their location in riparian areas, private lands, and PROWs. We applied three theories of household behavior—population, lifestyle behavior, and social stratification—to assess the relative significance of three levels of management—individual, household, and municipal—to the distribution of vegetation cover in these areas.

There are distinct mechanisms hypothesized to link population, lifestyle behavior theory, and social stratification to vegetation cover in riparian areas, private lands, and PROWs. Social science research has focused on theoretical explanations that consider either population density (see Agarwal and others 2002 for a comprehensive review in terms of land-use/land-cover models) or social stratification (Burch 1976; Choldin 1984; Logan and Molotch 1987; Grove 1996) as the primary driver of the distribution of vegetation in urban ecological systems. Population density is presumed to drive vegetative change in that, as an area is settled with more people, flora and fauna are displaced directly by roads and buildings and indirectly by pollution as the by-product of human activities. Social stratification theory has been used to explain vegetative patterns in that the relative power or influence that different urban neighborhoods have over public and private investments at the municipal level produces an inequitable distribution of green investments in the city. Wealthy residential neighborhoods are more likely to be characterized by (a) more homeowners and fewer renters and absentee landowners; (b) residents who are able to migrate to more desirable and healthy areas, who were effective at community organizing, and who are willing to become involved in local politics; and (c) elites who have differential access to government control over public investment, pollution control, and land-use decision making. In contrast, low-income and heavily populated minority areas are more likely to (a) be located in or next to polluted areas, (b) be unable to migrate to more desirable and healthy areas, and (c) have fewer human resources in terms of leadership, knowledge, political and legal skills, and communication networks to manipulate existing power structures (Logan and Molotch 1987).

A number of studies have used measures of income and education to examine the relationship between social stratification and vegetation structure (Whitney and Adams 1980; Palmer 1984; Grove 1996; Grove and Burch 1997; Dow 2000; Vogt and others 2002; Hope and others 2003; Martin and others 2004). Hope and others (2003) and Martin and others (2004) have proposed a ''luxury effect'' to explain the relationship between socioeconomic status and urban vegetation. This approach is limited by the underlying premise that there is a widespread and singular conception of luxury, regardless of a household's demography, ethnicity, culture, income, or education. Widespread examples of consumer market fragmentation and diverse lifestyle preferences make it clear that this is not the case (Solomon 1999; Weiss 2000; Holbrook 2001).

The concept of a luxury effect is relevant to the third social theory we discuss: lifestyle behaviors and an ecology of prestige (Grove and others 2004). Social differentiation among urban neighborhoods frequently becomes manifest in terms of the different lifestyle choices that households make and how those choices change over time. Some of the characteristics that affect the choices households make about where to locate include socioeconomic status, family size and life stage, and ethnicity (Timms 1971; Knox 1994; Short 1996; Gottdiener and Hutchinson 2001; Kaplan and others 2004). Building on this approach to lifestyle choices and neighborhood differentiation, we have proposed that many environmental management decisions and expenditures on environmentally relevant goods and services are motivated by group identity and the perception of social status associated with different lifestyles (Grove and Burch 2002; Grove and others 2004, 2006a,b forthcoming; Law and others 2004). In this case, a household's land management decisions are influenced by its desire to uphold the prestige of its community and outwardly express its membership in a given lifestyle group. From this perspective, housing and yard styles, green grass, and tree and shrub plantings are status symbols, reflecting the different types of neighborhoods to which people belong (Jenkins 1994; Scotts 1998; Robbins and others 2001; Robbins and Sharp 2003). These status symbols are not luxuries and vary among different lifestyle groups.

A critical element that may be missing from each of these social theories is a temporal component. Researchers have found that housing age is significantly associated with plant species composition (Whitney and Adams 1980), diversity (Hope and others 2003), abundance (Martin and others 2004), and lawn fertilizer applications (Law and others 2004). Researchers have also found a temporal lag between changes in neighborhood socioeconomic status and vegetation cover (Grove 1996; Vogt and others 2002). However, some urban foresters have disputed the significance of housing age, particularly in the case of older housing; indeed, they have described numerous examples of similar housing age and extreme differences in vegetation cover. They have also noted the absence of empirical studies of urban tree growth and mortality rates and successional dynamics for different types of urban forest management (Smith 2004; M. F. Glavin, personal communication).

A second critical element that may be missing from each of these social theories is a biocomplexity perspective—spatial, temporal, and organizational (sensu Pickett and others 2005)—particularly an awareness of organizational complexity. Organizational complexity, expressed spatially as the progression from within-unit processes to boundary regulation, cross-unit regulation, and functional patch dynamics, may be particularly important to this research because it assists in identifying and associating different levels of management with corresponding urban forest management types and social theory (Figure 1). Specifically, different levels of social organization may correspond to different vegetation types and social theories (Grove and Burch 1997; Grimm and others 2000; Vogt and others 2002). Figure 1 illustrates this potential organizational complexity, with riparian areas at

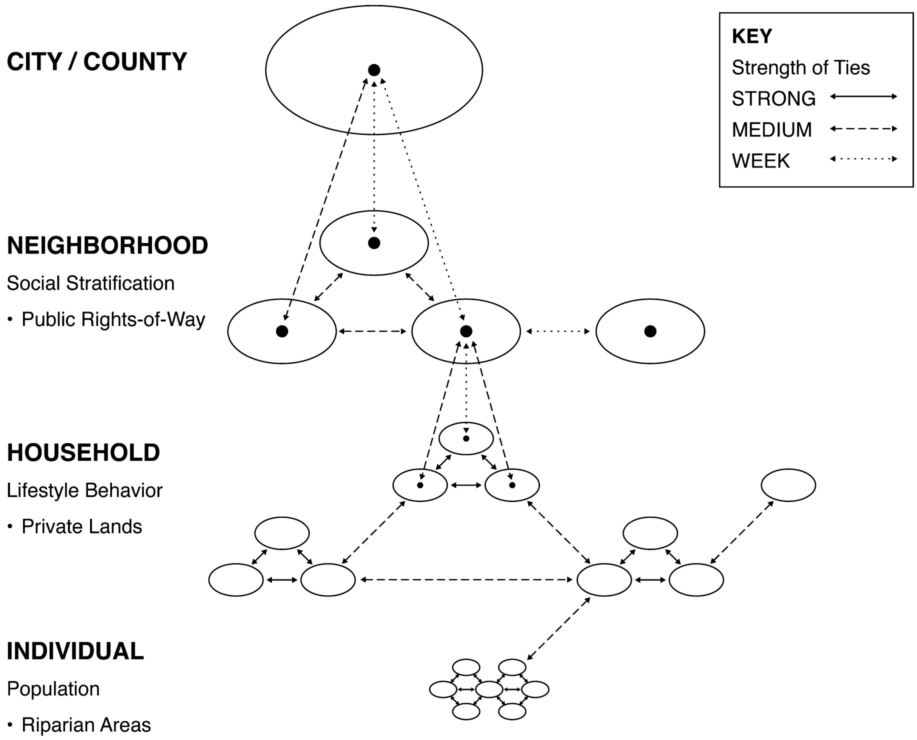

Figure 1. Hypothesized model of social organizational complexity in the Baltimore ecosystem Study.

the individual level associated with population theory, private lands at the household level associated with lifestyle behavior theory, and PROWs at the neighborhood level associated with social stratification theory. In other words, at different levels of social organization, different social processes may determine the distribution of vegetation cover. Further, by conceiving of the system as organizationally complex, we can examine how different social theories may be complementary rather than conflicting. This is important because it can provide a foundation for the generation of a new human ecosystem theory describing the reciprocal relationships among levels of organization (Grove and others 2005; Pickett and others 2005).

The empirical ability to examine and compare the relative significance of these three social theories—population, lifestyle behavior, and social stratification—associated with vegetation cover in riparian areas, private lands, and PROWs is new. Until recently, only relatively coarse-resolution geospatial data have been available to carry out such analyses. Regional vegetation-cover data have typically been derived from 30 m resolution Landsat Thematic Mapper (TM) satellite imagery. Socioeconomic analyses have normally been carried out at the level of a US census tract, in which a single tract contains approximately 2,500–8,000 persons, or a US census block group, which contains between 200 and 400 households. Other geospatial data, particularly cadastral information, have more often than not been maintained by local governments in hard-copy format. Recent advances in remote sensing and the widespread adoption of geographic information systems (GIS) by federal, state, and local governments have greatly increased the availability of high-resolution geospatial data. Vegetation can be derived from high-resolution imagery and combined with digital parcel data, which includes property boundaries for each parcel, and digital surface-water data to distinguish among vegetation in riparian areas, private lands, and PROWs. Figure 2 compares and contrasts the types of analyses that can be done with coarse-resolution data from Landsat-derived vegetation and US census block groups and high-resolution data from IKONOS-derived vegetation and parcel boundaries.

Research Question and Hypotheses

Based upon our summary of recent developments in theory and data, we ask, *What is the relative significance of population, lifestyle behavior, and social stratification theories to the distribution of vegetation cover—grass and trees—in riparian, private lands, and PROWs in urban ecological systems?* We propose four hypotheses:

H_1 *Population.* Population density will be most significant to the distribution of vegetation cover in riparian areas. This reflects the idea that only

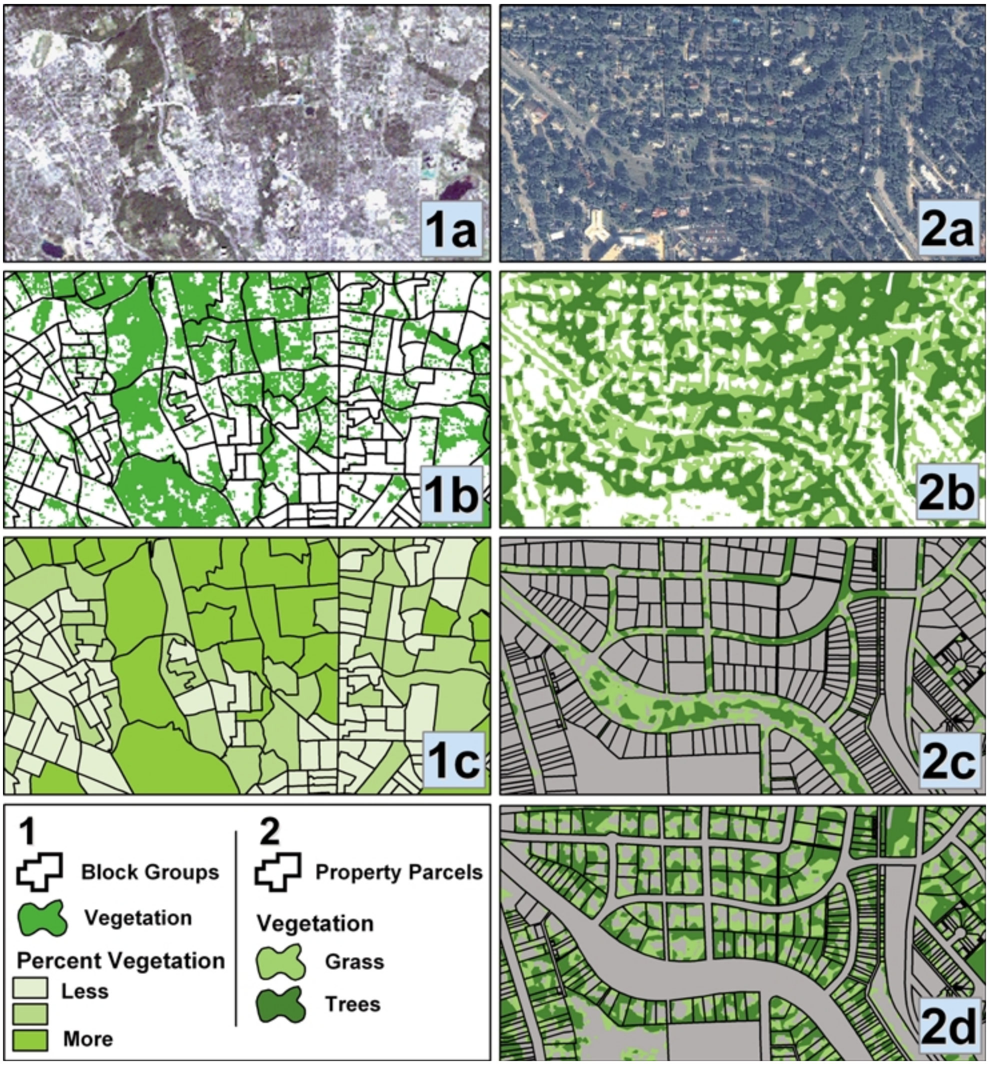

Figure 2. Comparison of relatively coarse-scale (1:100,000) and fine-scale (1:10,000) vegetation analysis that can be performed using Landsat-(**1**) and IKONOS-(**2**) derived vegetation data. The relatively coarse resolution of Landsat, at 30 m (**1a**, **1b**), only allows for vegetation summation at the block group level (**1c**). At 1 m, IKONOS satellite imagery (**2a**) provides a much more precise data source from which to derive vegetation (**2b**). When combined with parcel data, private land (**2c**) and public right of way (**2d**) vegetation can be distinguished. IKONOS imagery courtesy of Space Imaging, LLC.

recently have public agencies, community groups, and private homeowners identified vegetation management in urban riparian areas as an important issue (Maryland Forest Service 2004). Thus, the direct and indirect settlement effects associated with population density will be the most significant driver of vegetation cover in riparian areas.

H_2 *Lifestyle Behavior.* Lifestyle behavior will be most significant to the distribution of vegetation cover on private lands. A household's land management decisions are influenced by its desire to uphold the prestige of the community and express its membership in a given lifestyle group. This group can be interpreted as a manifestation of the household's placement in a lifestyle group, representing its group identity and social status.

H_3 *Social Stratification.* Social stratification will be most significant to the distribution of vegetation cover in PROWs. Public agencies are legally responsible for the management of vegetation in PROWs. The distribution of vegetation will be inequitable, reflecting the relative influence that neighborhoods have over municipal investment decisions.

H_4 *Housing Age.* Housing age will be significant to the distribution of vegetation cover in riparian areas, private lands, and PROWs. Land cover is dramatically altered when new homes are built in urban areas. Vegetation cover develops over time and reflects the time that has elapsed since it was established (Whitney and Adams 1980; Hope and others 2003). Because of disagreements among researchers (Whitney and Adams 1980; Hope and others 2003) and urban forestry professionals (M. F. Galvin, personal communication; Smith 2004), we propose that the relationship is nonlinear, with housing age being more significant when

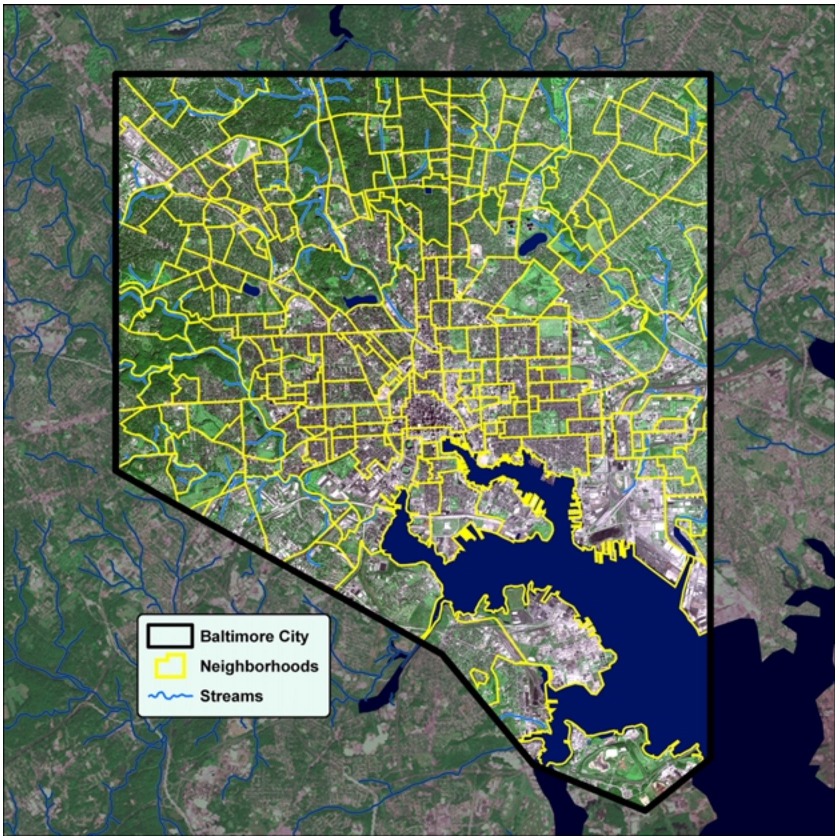

Figure 3. Site map of Baltimore City.

homes are new and less significant when homes are old.

METHODS

Site Description

Urban ecosystems are strikingly heterogeneous and scale dependent (Grimm and others 2000; Pickett and others 2001). Baltimore, Maryland (lower left: 39°11′31″N, 76P°42′38″W; upper right: 39°22′30″N, 76°31′42″W), houses 614,000 people in 276 neighborhoods (Figure 3). In 2000, the City of Baltimore had 258,518 households and 300,477 household building units, with an average of 2.5 persons per household. The city includes a variety of housing types, of which 14.8% are single-family detached units, 28.4% are multifamily units, and 55.6% are town homes. The median age of these housing units as summarized by the US census block group, is 58 years, with a median low of 4 years and a median high of 64 years. The city has experienced extensive demographic and economic changes over the past 50 years, with its population declining from nearly 1.2 million in the 1950s to its current level (Burch and Grove 1993). At the same time, the Baltimore metropolitan region has had one of the highest rates of deforestation in the northeastern United States because of urban sprawl (Horton 1987). Located in the deciduous forest biome, on the banks of the Chesapeake Bay, the nation's largest estuary, Baltimore City is drained by three major streams and a direct harbor watershed.

Databases

Categorization of Neighborhoods: Population, Lifestyle Behavior, and Social Stratification. Neighborhood measures of population, lifestyle behavior, and social stratification are based on the Claritas PRIZM (potential rating index for zipcode markets) categorization system, which was developed by demographers and sociologists for market research (Weiss 1988, 2000; Holbrook 2001; Grove and others, 2006a, forthcoming). There are two primary goals of the PRIZM classification system. First is to categorize the 250 million people of the American population and their urban, suburban, and rural neighborhoods into lifestyle clusters using census data about household education, income, occupation, race/ancestry, family composition, and housing. Second is to associate these clusters with characteristic household tastes and attitudes using additional data such as market research surveys, public opinion polls, and point-of-purchase receipts (Weiss 1988, 2000).

Claritas uses factor analysis and US census data to generate several group measures. This process is also known as ''social area analysis'', an urban studies method employing factor analysis (Bell and Newby 1976; Johnston 1976; Murdie 1976; Hamm 1982). Claritas has identified six primary factors that explain neighborhood variance: social rank (for example, income, education), household (for example, life stage, size), mobility (for example, length of residence), ethnicity (for example, race, foreign versus U.S. born), urbanization (for example, population and housing density), and housing (for example, owner versus renter status, home values) (Lang and others 1997; Claritas 1999). The PRIZM categorization system has three levels of aggregation: 5, 15, or 62 categories. The five-group categorization is arrayed along an axis of urbanization. Disaggregating from 5 to 15 categories adds a second axis: socioeconomic status. The 62-group categorization disaggregates the socioeconomic status axis into a lifestyle categorization with components including household composition, mobility, ethnicity, and housing characteristics (Claritas 1999). The three PRIZM aggregations—urbanization, socioeconomic status, and lifestyle—correspond, respectively, to population density, social stratification, and lifestyle behavior—the three theories we suggest influence the distribution of vegetation cover. To date, PRIZM has been used in several studies of urban vegetation, including Martin and others (2004), Grove and others (2006).

A GIS data layer of PRIZM categories was created for Baltimore City by joining US Census Block Group boundaries data from geographic data technology's (GDT) dynamap census data with a PRIZM classification for each block group from the Claritas 2003 database (http://www.claritas.com). Each of the 710 block groups was assigned a unique PRIZM category. The GDT census boundaries were used instead of the US Census Bureau and Claritas boundaries because of their higher positional accuracy when compared with 1:12,000-scale IKONOS imagery. The Baltimore City boundary derived from the GDT census data served as the common boundary for all geospatial operations.

Median House Age. Median house age for each block group was obtained from the Geolytics census 2000 attribute database (Geolytics 2000), and each block group was assigned a median house age value. Land-use history was not included in this analysis because the current land use in Baltimore City was in place or had been converted from agricultural use by the early 1900s (Besley 1914, 1916).

Parcel Boundaries. Property parcel boundaries were obtained from the City of Baltimore. These parcel boundaries, converted to digital format from the city's cadastral maps, were current as of July 2001. Although the City of Baltimore does not document the accuracy of the parcel data set, the parcel polygons were overlaid on top of 1:12,000-scale 1m IKONOS imagery. Fifty parcel/PROW boundaries that could be seen clearly on the IKONOS imagery were compared to the parcel polygons. A mean difference of approximately ± 2 pixels (2 m) between the two data sets was noted. The Baltimore city parcel data did not have the same geographic extent as the block group data, with parcels either extending across the city's border or falling short of it. Where city parcel boundaries fell short of the city boundary, parcel data from Baltimore County were appended to the city data.

Vegetation Data. The vegetation data used in this study came from the strategic urban forests assessment (SUFA) for Baltimore City (Irani and Galvin 2003). Four land-cover classes were derived from 1:12,000 scale IKONOS satellite imagery (Space Imaging, LLC) acquired in October 2001: other (developed), grass, forest, and water. After fusing the 1 m panchromatic imagery with the 4 m imagery to create a pan-sharpened 1 m multispectral image, Irani and Galvin (2003) applied a series of algorithms to extract land cover. At the time of this publication, no information was available on the accuracy of the classification. However, a qualitative assessment of the accuracy indicated that there was generally excellent discrimination between the other, vegetation (forest and grass), and water classes.

Hydrologic Data. Hydrologic data were obtained from two sources: (a) 1:24,000-scale hydrologic data from the United States Geological Survey (USGS) and (b) water features depicted in the SUFA LULC data set (see above). A comparison of the two data sets with 2001 1 m pan-sharpened multispectral IKONOS imagery indicated that the SUFA LULC data set provided a more precise delineation of water feature boundaries (stream, lake, and harbor banks). However, many lower-order streams that exist in the USGS data set were not present in the SUFA data set. In an effort to create the optimal water data set, water-feature boundaries from the SUFA data set were combined with the stream centerlines from the USGS data set. Using the IKONOS imagery as the reference data set, editing was performed to ensure that all streams were connected and to correct positional errors that existed in the USGS stream centerlines data set. Finally, water features were assigned one of the following codes: stream centerline, stream shoreline, pond/lake shoreline, or harbor shoreline.

Geographical Analyses

Segmentation of Vegetation and Characterization of US Census Block Groups. Riparian vegetation, private-land vegetation, and PROW vegetation were each summarized at the block group level following a three-step process: (a) thematic polygon (riparian area, private land, PROW) boundaries were extracted and created from source data, (b) the thematic polygon boundaries were combined with forest and grass vegetation polygons from Maryland Dept. of Natural resources (DNR's) SUFA vegetation layer, and (3) thematic boundary area and vegetation area were summarized and normalized at the block group level.

Four separate riparian buffer analyses were carried out: (a) 100 ft (30.5 m) buffer around all streams (centerlines and shorelines), (b) 100 ft buffer around all water features, (c) 300 ft (91.5 m) buffer around all streams, and (d) 300 ft buffer around all water features. The choice of buffer size was based on riparian guidelines for water quality (100 ft) and wildlife habitat (300 ft) of streams established by the State of Maryland (Goetz and others 2003; Maryland Forest service 2004; A. Hairston-Strang, personal communication 2004; M. F. Galvin, personal communication). Nonstream riparian areas were included to examine their significance to the results. Each of the four buffered layers was individually intersected with both the forest and grass polygons from the SUFA LULC data set and the block group boundaries. The result of this intersection was a layer in which only those vegetation polygons that fell within the buffer remained, each of which was assigned a block group identifier. This enabled for the summation of riparian forest area and riparian grass area by block group for each of the four methods. A parallel analysis was done to compute the riparian area for each block group. Each of the four riparian buffer layers was intersected with the block group layer, resulting in a layer consisting only of riparian polygons, each polygon assigned to one block group. The riparian area was then summarized for each block group. Finally, riparian forest area and riparian grass area were normalized to percentages at the block group level by dividing by the total area of riparian land within the block group.

PROW land was extracted from the parcel boundary data set by identifying all ''nonparcel'' polygons. As implied, no parcels exist in ''nonparcel'' areas. In Baltimore these nonparcel areas correspond to roads and the rights-of-way along roads. Railroad and transmission lines parcels are privately owned and not considered PROW land. Topology rules were created to detect nonparcel areas, create new polygons from the gaps in the data set, then assign these polygons to the PROW category. As was done with the riparian analysis, the PROW layer was intersected with both the forest and grass polygons and the block group boundaries in one step and only the block group boundaries in another. PROW forest and grass areas were normalized at the block group level by dividing by the total area of PROW land within each block group.

For the private-land vegetation summarization, the parcel boundaries were first linked to the 2003 Maryland property view assessment and taxation database through a relational join to obtain land-use codes. Only those parcels with land-use codes aside from ''exempt'' and ''exempt commercial'' were retained for the private-land analysis. Approximately 70% of Baltimore City's parcel land fell into the ''private land'' category. However, the amount of exempt and exempt commercial land varied at the block group level, with the majority of block groups' parcel land being less than 30% exempt/exempt commercial (median = 16%, mean = 23%). As with the two previous analyses, the private-lands layer was intersected with the forest and grass polygons from the SUFA layer and the block group boundaries in one step and only the block group boundaries in another. The forest and grass private-land areas were normalized at the block group level by dividing by the total private land area in the block group.

A summary of the area occupied by riparian areas, private lands, and PROWs is presented in Table 1. On average, riparian land occupied less than 0.1% of the block group area, PROW land 19%, and private land 55%. Due to errors in the parcel data, private land was overestimated and PROW land underestimated for three block groups in the city that occupied less than 1% of the total area under study. These three block groups were retained in the analyses. A total of 710 block groups were used in the analyses. Riparian areas were included in 169 block groups based on 100 ft buffers around streams only, in 228 block groups using a 300-ft buffer around all water features; 707 block

Table 1. Summary of Area Statistics for Block Groups along with Riparian Areas, Private Land, and Public Right-of-Way (PROW)

	Area (ha)			
Unit of Analysis	**Mean**	**SD**	**Min.**	**Max.**
Block group	29.71	51.50	3.01	881.96
Riparian areas	0.96	2.77	0.00	22.70
Private lands	16.37	30.00	0.00	16.37
PROWs	6.22	6.39	0.00	93.32

groups contained PROWs; and 710 block groups had private lands present.

Statistical Analyses. A series of 28 logistic regressions were performed and compared to determine which combinations of PRIZM categorization (5, 15, or 62 categories) and median house age best predicted variation in each of four response variables (percent PROW tree and grass cover and percent private tree and grass cover). Twenty-four additional logistic regressions were performed and compared to determine which PRIZM categorization best explained variation in each of eight response variables related to riparian vegetation. In a logistic regression, a response variable that is binary or a rate ranging between 0 and 1 is predicted as a function of a series of continuous or discrete predictor variables. Logistic regression uses a maximum-likelihood estimator that converts the dependent variable into a logit variable, or the natural log odds of the response occurring. In this case, our predictor variables are all discrete, each representing a dummy variable for a different PRIZM category. This yields the following equation:

$$E\{Y\} = \frac{\exp\left(\beta_0 + \beta_1 X_1 + \cdots + \beta_{p-1} X_{p-1}\right)}{1 + \exp\left(\beta_0 + \beta_1 X_1 + \cdots + \beta_{p-1} X_{p-1}\right)} \quad (1)$$

where $E\{Y\}$ is the expected response value, β_0 is an intercept variable, and β_n is the coefficient representing estimated odds ratio for variable X_n holding all else constant. Logistic regression was used rather than linear regression or analysis of variance (ANOVA) because our response variable is a percentage. Not only do percentages tend to violate the assumptions of normality (normal distribution of responses for each category level), but they are also bounded between 0 and 1, whereas predictions from regression and ANOVA are not bounded. Although logistic regression is typically used for regressing binary (0, 1) response variables, it has been found to be superior in its predictive power to linear-regression approaches when the response is a percentage (Zhao and others 2001). This is partly because linear-regression models have increasingly poor predictive abilities as the actual value approaches the bounds of 1 and 0. A particular problem is that solving a linear model can result in values outside of those bounds. Although logistic regression is generally used with continuous predictors, it has been used successfully with categorical predictors and found to perform better than ANOVA under certain conditions (Whitmore and Schumacker 1999). PRIZM categories are coded as factors, and each category for a given PRIZM categorization is treated as a factor level or dummy variable, so a significance test statistic for a given factor can be interpreted as a test that the mean response for that group is significantly different than for the entire population. In the models where it is included, median housing age is coded as a quadratic term (the untransformed term plus the term squared).

We used the multimodel inference approach of Burnham and Anderson (2002) to determine whether PRIZM's 15 or 62 classifications, median housing age, or some combination best explained the variation in each of the 28 private-land and PROW response variables. We used similar methods to determine whether PRIZM's 15 or 62 classifications best explained the variation in each of the 24 riparian response variables (Table 2). Hence, for private-land and PROW models, we have groupings of seven comparative models for each response variable; whereas for the riparian variables, we have groupings of three comparative models for each response variable. In no case are two models with different response variables compared. For the models with median housing age by block group, a quadratic term for age is included, to account for our hypothesis that the effect of age on vegetation is nonconstant. Multimodel comparisons indicated that, in almost all cases, the model with the quadratic term was superior to those without; hence, for the sake of simplicity, only results with the quadratic term are given here.

Table 2. Summary Response and Predictor Variables of Logistic Regression Models

Name	Response	Predictors
PROWT1	Percentage of PROW covered by trees	PRIZM5
PROWT2	''''	PRIZM15
PROWT3	''''	PRIZM62
PROWT4	''''	AGE
PROWT5	''''	PRIZM5+AGE
PROWT6	''''	PRIZM15+AGE
PROWT7	''''	PRIZM62+AGE
PROWG1	Percentage of PROW covered by grass	PRIZM5
PROWG2	''''	PRIZM15
PROWG3	''''	PRIZM62
PROWG4	''''	AGE
PROWG5	''''	PRIZM5+AGE
PROWG6	''''	PRIZM15+AGE
PROWG7	''''	PRIZM62+AGE
PLT1	Percentage of private land covered by trees	PRIZM5
PLT2	''''	PRIZM15
PLT3	''''	PRIZM62
PLT4	''''	AGE
PLT5	''''	PRIZM5+AGE
PLT6	''''	PRIZM15+AGE
PLT7	''''	PRIZM62+AGE
PLG1	Percentage of private land covered by grass	PRIZM5
PLG2	''''	PRIZM15
PLG3	''''	PRIZM62
PLG4	''''	AGE
PLG5	''''	PRIZM5+AGE
PLG6	''''	PRIZM15+AGE
PLG7	''''	PRIZM62+AGE
RTa1	Percentage of areas within 100 ft of streams covered by trees	PRIZM5
RTa2	''''	PRIZM15
RTa3	''''	PRIZM62
RGa1	Percentage of areas within 100 ft of streams covered by grass	PRIZM5
RGa2	''''	PRIZM15
RGa3	''''	PRIZM62
RTb1	Percentage of areas within 100 ft of all water bodies covered by trees	PRIZM5
RTb2	''''	PRIZM15
RTb3	''''	PRIZM62
RGb1	Percentage of areas within 100 ft of all water bodies covered by grass	PRIZM5
RGb2	''''	PRIZM15
RGb3	''''	PRIZM62
RTc1	Percentage of areas within 300 ft of streams covered by trees	PRIZM5
RTc2	''''	PRIZM15
RTc3	''''	PRIZM62
RGc1	Percentage of areas within 300 ft of streams covered by grass	PRIZM5
RGc2	''''	PRIZM15
RGc3	''''	PRIZM62
RTd1	Percentage of areas within 300 ft of water bodies covered by trees	PRIZM5
RTd2	''''	PRIZM15
RTd3	''''	PRIZM62
RGd1	Percentage of areas within 300 ft of water bodies covered by grass	PRIZM5
RGd2	''''	PRIZM15
RGd3	''''	PRIZM62

PROW, public rights-of-way.

Burnham and Anderson's (2002) approach relies on the information theory approach pioneered by Akaike (1973, 1978), which shows that minimization of the Akaike information criterion (AIC) can help to select the ''order'' of likelihood of a set of nested or nonnested models. The more commonly used *F*-tests can only be used for nested models. That is, for *k* possible models of an underlying process, AIC scores help to tell us which of those models approximate that underlying process the best. Traditional model fit metrics, such as *R*-squared, are often not appropriate for comparison because a model with more variables is by definition more statistically ''flexible'' than one with fewer (which is why *R*-squared will always go up with the addition of parameters), meaning that the more complex model will always appear superior. However, complexity comes at the expanse of parsimony; therefore, it is commonly accepted that a better model is one that increases fit relative to the number of parameters (Myung and others 2000; Wagenmakers and Farrell 2004). On the other hand, AIC, penalizes models that are less parsimonious. By accounting for the tradeoff between model fit and complexity, it can show us which models best compromise between the two. The AIC is given by the equation (Burnham and Anderson 2002; Turkheimer and others 2003):

$$\mathrm{AIC} = -2 \log L(M) + 2k \tag{2}$$

where k is the number of parameters plus one and $\log L(M)$ is the maximized log likelihood for the fitted model.

The AIC cannot be interpreted on its own, but only as a relative measure, to be compared to the AIC scores for other models. If the AIC score from model A is lower than that for model B, it is an indication that model A is more likely to be correct. However, although a lower AIC is an indication of a more likely model, that information does not explain how much more likely one model is over another, and in some cases small differences in AIC scores can lead to a false sense of confidence that one model is better than another (Wagenmakers and Farrell 2004). Akaike weights (Burnham and Anderson 2002) show the probability of the more complex model being the correct one and are given by the equation:

$$w_i(\mathrm{AIC}) = \frac{\mathrm{e}^{-.5(\Delta_i(\mathrm{AIC}))}}{\sum_{\mathrm{k}=1}^{\mathrm{K}} \mathrm{e}^{-.5(\Delta_i(\mathrm{AIC}))}} \tag{3}$$

where k is the number of models.

Results

In reporting our results, we use population density, social stratification, and lifestyle behavior to signify the PRIZM system aggregated to 5, 15, and 62 categories respectively. Table 3, which includes results for models with private-land and PROW response variables, shows that the most complex model—lifestyle behavior and housing age—best explains PROW grass, private-land trees, and private-land grass, indicating that the loss in parsimony from greater model detail is outweighed by increases to model fit. For PROW trees, on the other hand, the third model—lifestyle behavior—is listed as best, indicating that any gains to fit made by adding house age are outweighed by losses to model parsimony (this result held even if the quadratic term for house age was not included). The seven-way Akaike weights suggest that there is little probability that the second-best model is actually the best in any of the cases.

The order of the models is also illustrative in teasing out the relative contribution of the different explanatory variables. For PROW trees, the fact that model 7, lifestyle behavior and house age, is second, despite housing age not significantly improving on the model, suggests the importance of lifestyle behavior relative to population density and social stratification. For PROW and private-land grass, the fact that model 6—social stratification and housing age—is second best suggests that housing age may be a more important contributor in making model 7 the best, whereas for private-land trees, the fact that model 3—lifestyle behavior—is second suggests the relative importance of lifestyle behavior in doing the same.

In addition, pseudo R-squared values on model 4, housing age only—tend to be much higher for grass (0.12 and 0.19 for PROW and private land, respectively) than for trees (0.06 and 0.09) (Table 4).

For the models with riparian-land response variables (Table 4), the simplest model—population density—is always identified as the best, no matter how riparian buffers are specified. However, this does not prove that population density is necessarily an adequate predictor of riparian vegetation. Rather, it suggests that we fail to prove that social stratification or lifestyle behavior adds any significant explanatory power, relative to the loss of parsimony they introduce. Very low pseudo *R*-squared values on the models with just population density suggest that if it is an important predictor, our models have failed to capture population

Table 3. Summary Results for Logistic Regression Models for Private Land and public Rights-of-way PROW Including AIC Scores, Seven-way Akaike Weights, Model Rankings, and Pseudo *R*-squared Values

Response Variable	Model Name and Terms	Residual df	Residual Deviance	Log-likelihood	AIC	Dierence from Best Model	Rank	Akaike Weight (%)	Pseudo R-squared
PROW trees	PROWT1: PRIZM5	706	73.52	−210.11	430.21	38.14	6	0.000	0.07
	PROWT2: PRIZM15	700	63.73	−212.70	447.41	55.33	7	0.000	0.20
	PROWT3: PRIZM62	681	56.90	−166.04	392.08	0.00	1	99.780	0.29
	PROWT4: AGE	707	74.01	−210.78	429.56	37.48	5	0.000	0.06
	PROWT5: PRIZM5+AGE	704	70.38	−204.00	421.99	29.91	3	0.000	0.11
	PROWT6: PRIZM15 + AGE	698	58.84	−200.09	426.18	34.11	4	0.000	0.26
	PROWT7: PRIZM62 + AGE	679	52.38	−170.16	404.31	12.24	2	0.220	0.35
PROW grass	PROWG1: PRIZM5	706	49.62	−56.81	123.62	188.40	7	0.000	0.05
	PROWG2: PRIZM15	700	44.29	−20.83	63.66	128.43	6	0.000	0.15
	PROWG3: PRIZM62	681	39.91	26.69	6.63	71.41	3	0.000	0.24
	PROWG4: AGE	707	45.73	−24.80	57.60	122.37	5	0.000	0.12
	PROWG5: PRIZM5+AGE	704	44.52	−11.77	37.55	102.32	4	0.000	0.15
	PROWG6: PRIZM15+AGE	698	39.18	31.37	−36.74	28.03	2	0.000	0.25
	PROWG7: PRIZM62+AGE	679	35.94	64.39	−64.78	0.00	1	100.000	0.32
Private land trees	PLT1: PRIZM5	706	111.58	−351.34	712.68	47.83	6	0.000	0.09
	PLT2: PRIZM15	700	100.63	−353.89	729.77	64.92	7	0.000	0.17
	PLT3: PRIZM62	681	89.72	−309.42	678.83	13.98	2	0.092	0.28
	PLT4: AGE	707	108.59	−349.57	707.14	42.28	5	0.000	0.09
	PLT5: PRIZM5 + AGE	704	103.93	−338.02	690.03	25.18	3	0.000	0.13
	PLT6: PRIZM15 + AGE	698	90.63	−332.90	691.79	26.94	4	0.000	0.25
	PLT7: PRIZM62 + AGE	679	80.81	−300.43	664.85	0.00	1	99.908	0.34
Private land grass	PLG1: PRIZM5	706	62.64	−142.53	295.06	195.36	7	0.000	0.06
	PLG2: PRIZM15	700	58.18	−117.34	256.68	156.99	6	0.000	0.13
	PLG3: PRIZM62	681	51.82	−70.11	200.21	100.52	5	0.000	0.23
	PLG4: AGE	707	53.96	−87.07	182.14	82.45	4	0.000	0.19
	PLG5: PRIZM5+AGE	704	51.92	−72.34	158.68	58.98	3	0.000	0.23
	PLG6: PRIZM15+AGE	698	47.99	−47.11	120.22	20.52	2	0.003	0.29
	PLG7: PRIZM62+AGE	679	43.98	−17.85	99.70	0.00	1	99.997	0.35

AIC, Akaike Information Criterion.

Table 4. Summary Results for Logistic Regression Models for Riparian Land Including AIC Scores, three-way Akaike Weights, Model Rankings, and Pseudo *R*-squared Values

Response Variable	Model Name	Model terms	Residual df	Residual deviance	Log-likelihood	AIC	Dierence from Best Model	Rank	Akaike Weight (%)	Pseudo R-squared
Riparian forest—100-ft buffer of streams	RFa1	PRIZM5	706	272.79	−692.80	1395.59	0.00	1	100	0.0491
	RFa2	PRIZM15	700	257.72	−730.08	1482.16	86.57	2	0	0.1117
	RFa3	PRIZM62	681	242.05	−720.99	1501.98	106.38	3	0	0.1754
Riparian Grass—100-ft buffer of streams	RGa1	PRIZM5	706	134.75	−440.41	890.82	0.00	1	100	0.0414
	RGa2	PRIZM15	700	129.36	−458.73	939.46	48.63	2	0	0.0833
	RGa3	PRIZM62	681	122.53	−459.20	978.41	87.59	3	0	0.1360
Riparian Forest—100-ft buffer of all water bodies	RFb1	PRIZM5	706	267.30	−682.81	1375.62	0.00	1	100	0.0414
	RFb2	PRIZM15	700	252.20	−720.84	1463.69	88.07	2	0	0.1057
	RFb3	PRIZM62	681	236.09	−712.60	1485.19	109.57	3	0	0.1728
Riparian Grass—100-ft buffer of all water bodies	RGb1	PRIZM5	706	139.91	−448.03	906.07	0.00	1	100	0.0308
	RGb2	PRIZM15	700	131.67	−467.71	957.43	51.36	2	0	0.0933
	RGb3	PRIZM62	681	124.71	−466.21	992.42	86.36	3	0	0.1455
Riparian Forest—300-ft buffer of streams	RFc1	PRIZM5	706	236.26	−627.84	1265.68	0.00	1	100	0.0476
	RFc2	PRIZM15	700	223.50	−654.16	1330.32	64.64	2	0	0.1076
	RFc3	PRIZM62	681	210.50	−638.58	1337.16	71.48	3	0	0.1675
Riparian Grass—300-ft buffer of streams	RGc1	PRIZM5	706	159.65	−501.50	1013.00	0.00	1	100	0.0725
	RGc2	PRIZM15	700	154.55	−517.15	1056.31	43.30	2	0	0.1054
	RGc3	PRIZM62	681	149.43	−505.07	1070.15	57.15	3	0	0.1383
Riparian Forest—300-ft buffer of all water bodies	RFd1	PRIZM5	706	232.45	−621.33	1252.66	0.00	1	100	0.0434
	RFd2	PRIZM15	700	219.02	−646.04	1314.08	61.43	2	0	0.1076
	RdF3	PRIZM62	681	206.21	−630.19	1320.37	67.72	3	0	0.1677
Riparian Grass—300-ft buffer of all water bodies	RGd1	PRIZM5	706	165.52	−506.57	1023.15	0.00	1	100	0.0581
	RGd2	PRIZM15	700	157.73	−519.08	1060.16	37.02	2	0	0.1076
	RGd3	PRIZM62	681	152.81	−505.70	1071.40	48.25	3	0	0.1384

Table 5. House Age Coefficients, *t* Statistics, and Significance Levels from Private Land and public Rights-of-way (PROW) Logistic Regression Models

Age Coefficients	House Age	*t*	House Age^2	*t*
PROWT4: AGE	0.126	1.135	−0.001520	−1.368
PROWT5: PRIZM5 + AGE	0.112	0.992	−0.001336	−1.178
PROWT6: PRIZM15 + AGE	0.162	1.302	−0.001881	−1.513
PROWT7: PRIZM62 + AGE	0.141	1.062	−0.001700	−1.287
PROWG4: AGE	0.123	1.563	−0.001407	−1.798[1]
PROWG5: PRIZM5 + AGE	0.119	1.494	−0.001347	−1.700
PROWG6: PRIZM15 + AGE	0.118	1.443	−0.001345	−1.657[1]
PROWG7: PRIZM62 + AGE	0.094	1.169	−0.001115	−1.383
PLT4: AGE	0.138	1.612	−0.001688	−1.962[2]
PLT5: PRIZM5 + AGE	0.125	1.437	−0.001525	−1.743[1]
PLT6: PRIZM15 + AGE	0.158	1.676[1]	−0.001898	−2.006[2]
PLT7: PRIZM62 + AGE	0.123	1.295	−0.001572	−1.650[1]
PLG4: AGE	0.166	2.180[2]	−0.001883	−2.499[2]
PLG5: PRIZM5 + AGE	0.161	2.096[2]	−0.001818	−2.387[2]
PLG6: PRIZM15 + AGE	0.154	1.980[2]	−0.001749	−2.275[2]
PLG7: PRIZM62 + AGE	0.126	1.655[1]	−0.001474	−1.940[1]

[1]*Significant at 90% confidence level.*
[2]*Significant at 95% confidence level.*

density's importance (possibly because PRIZM records it as a categorical rather than continuous variable). The role of population density as a predictor should be further explored.

Coefficients and test statistics for the age terms in the models where they appear are provided in Table 5. In the interest of space, coefficients on PRIZM categories are not given. The first two columns of Table 5 contain coefficients and Wald test statistics for the median housing age variable; and the second two columns contain the same for the squared term for that variable. In all cases, the coefficient on the untransformed variable is positive, ranging between 0.094 and 0.16, whereas in all cases, the squared term is negative, ranging between –0.0011 and –0.0018. The stars next to the test statistics indicate that the squared term is significant at the 95% confidence level (according to a Wald test) for most but not all of the private-land models, whereas none are significant for the PROW models. Moreover, the untransformed term is insignificant for all but the private-land grass models. This result is somewhat inconsistent with the AIC model comparisons, which indicated that in all cases but PROW trees, median housing age improves the model, and that in most cases, the quadratic term also improves the model over a simple linear term for housing age.

To address this inconsistency, we ran a series of quasi-likelihood regressions on all models, including housing age. The logistic regression model assumes a binomial distribution of errors which, especially in the case of proportion data, may not always be the case. It is possible that this is partly to blame for overinflation of standard errors, and hence lower than expected test statistics on coefficients. A less restrictive generalized linear model uses ''quasi-likelihood'' estimation, which requires definition of only the mean and variance function without assuming a specific distribution (McCullagh and Nelder 1989). It is frequently warranted in cases where data are highly underdispersed or overdispersed and has been used on percentage data (Wedderburn 1974). This approach requires the user to specify a link and variance function. For this model, we chose logit for the former, because our data are bounded by 0 and 1, and constant variance for the latter, because residual plots indicated little pattern to the spread of errors.

The resulting coefficients and test statistics show a very similar range for coefficients, but much higher *t* statistics overall (Table 6). The fact that the coefficients on housing age terms for PROW tree models are significant is not necessarily inconsistent with the fact that model 3—lifestyle behavior—has the lowest AIC score, because its explanatory power might be outweighed by its penalty to parsimony. All coefficients are significant at the 95% confidence level, and all but one are significant at the 99% level.

The signs on the two age variables suggest a parabolic relationship between housing age and the probability of presence of vegetation, holding

Table 6. House Age Coefficients, *t* Statistics, and Significance Levels from Private Land and Public Rights of way (PROW) Quasi Likelihood Regression Models

Age Coefficients	House Age	*t*	House Age^2	*t*
PROWT4: AGE	0.118	2.886[2]	−0.001461	−3.522[2]
PROWT5: PRIZM5 + AGE	0.083	2.140[1]	−0.001024	−2.622[2]
PROWT6: PRIZM15 + AGE	0.122	3.539[2]	−0.001466	−4.195[2]
PROWT7: PRIZM62 + AGE	0.083	2.426[2]	−0.001097	−3.181[2]
PROWG4: AGE	0.181	6.950[2]	−0.001957	−7.736[2]
PROWG5: PRIZM5 + AGE	0.180	6.864[2]	−0.001921	−7.557[2]
PROWG6: PRIZM15 + AGE	0.174	7.239[2]	−0.001877	−8.029[2]
PROWG7: PRIZM62 + AGE	0.141	5.942[2]	−0.001546	−6.696[2]
PLT4: AGE	0.129	3.542[2]	−0.001612	−4.365[2]
PLT5: PRIZM5 + AGE	0.108	2.981[2]	−0.001339	−3.678[2]
PLT6: PRIZM15 + AGE	0.142	4.158[2]	−0.001727	−5.018[2]
PLT7: PRIZM62 + AGE	0.091	2.830[2]	−0.001241	−3.819[2]
PLG4: AGE	0.192	7.993[2]	−0.002135	−9.050[2]
PLG5: PRIZM5 + AGE	0.190	7.791[2]	−0.002091	−8.758[2]
PLG6: PRIZM15 + AGE	0.172	7.613[2]	−0.001927	−8.668[2]
PLG7: PRIZM62 + AGE	0.135	6.137[2]	−0.001547	−7.153[2]

[1]*Significant at 95% confidence level.*
[2]*Significant at 99% confidence level.*

PRIZM class constant. Because the dependent variables represent the probability that there will be 100% tree or grass cover, we can interpret them as expected percentage tree or grass cover proxies. Hence, Figure 4A (tree cover) and B (grass cover) show how, under quasi-likelihood estimation, expected cover increases and then decreases in a parabolic fashion with housing age. The maximum occurs between 40 and 50 years. This does not necessarily mean that houses lose vegetation as they age beyond 40 or 50 years; rather, it means that houses built at that time are associated with lower vegetation levels for any number of reasons. Although not shown here, the curves derived from the logistic regression are extremely similar.

Discussion

Theoretical Implications

The results from our analyses indicate that we should accept hypotheses 2 and 4 and reject hypotheses 1 and 3. In other words, lifestyle behavior was the best predictor of vegetation cover on private lands, and median housing age was significantly associated with vegetation cover for riparian areas, private lands, and PROWs. Although population density was the best predictor of vegetation cover for riparian areas, the pseudo *R*-squared values were so low that it casts doubt on the model. Finally, social stratification was not the best predictor of vegetation cover in PROWs.

The poor performance of the population density model for all four combinations of riparian areas makes it clear that alternative theories and models are needed. For instance, historical legacies of zoning and development in riparian areas may exist. Also, larger-scale ecosystem processes, such as changes in riparian groundwater flow and associated urban hydrologic drought may play a significant role in the distribution of vegetation cover in riparian areas (Lowrance and others 1997; Groffman and others 2003).

Lifestyle behavior and median housing age were the best predictors of the distribution of vegetation cover on private lands. This suggests that household land management decisions, influenced by a household's desire to assert its membership in a given lifestyle group and to uphold the prestige of the household's neighborhood, best predicts variations in vegetation cover on private lands.

In most cases, public agencies are responsible for the maintenance of existing trees in PROWs, and homeowners are responsible for the maintenance of existing grass in these areas. Surprisingly, social stratification was not the best predictor of vegetation cover for PROWs. Rather, lifestyle behavior was a better predictor of the distribution of tree cover, and lifestyle behavior and median housing age was a better predictor of grass cover in PROWs. To explain this phenomenon, we hypothesize that homeowners invest both in their own property—private lands—and in the PROWs in front of

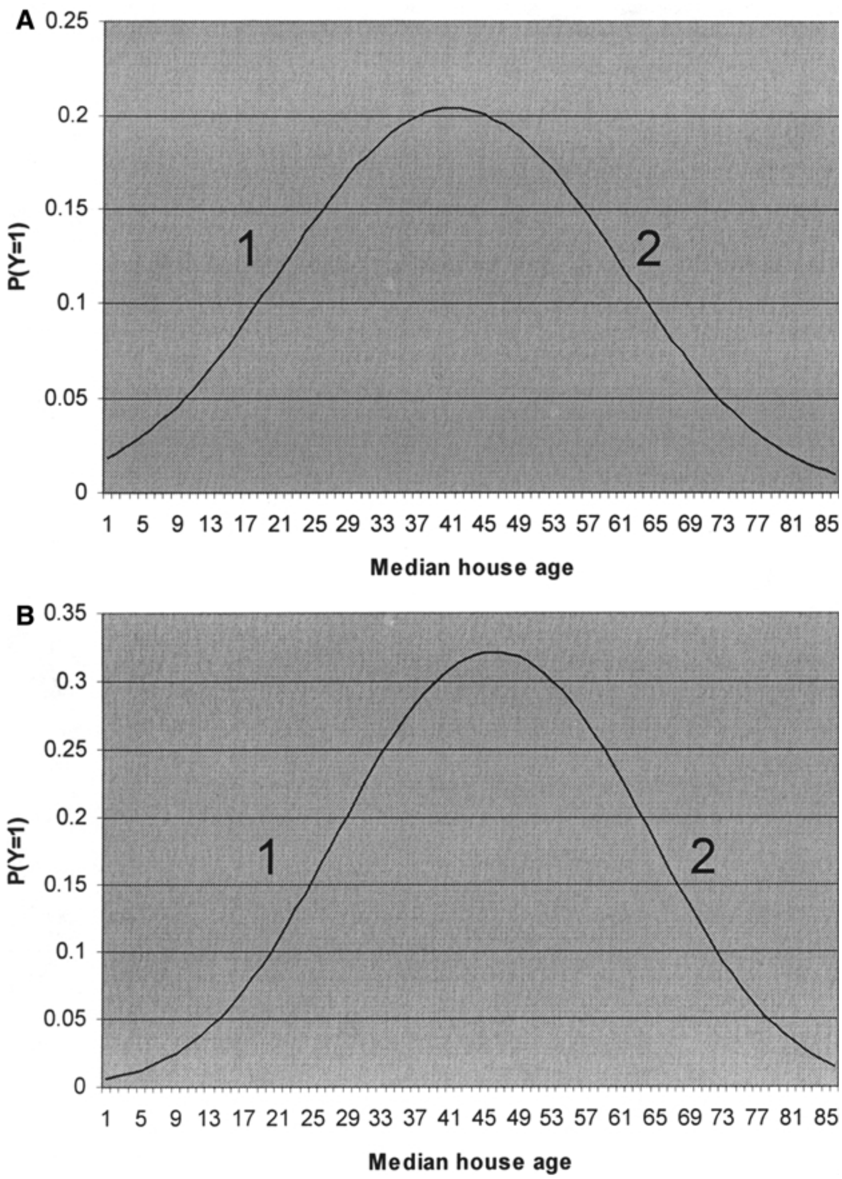

Figure 4a. Probability that tree cover is equal to 100% on private land as a function of median age of block group, based on quasi-likelihood logit regression. **4b** Probability that grass cover is equal to 100% on private land as a function of median age of block group, based on quasi-likelihood logit regression.

their house. This result is consistent with our hypotheses for private lands, given that the appearance of a household's property is affected by both the land around the home and the PROWs in front of the house.

Results for both private lands and PROWs are consistent with previous research that found socioeconomic status to be an important predictor of vegetation in urban residential areas (Whitney and Adams 1980; Palmer 1984; Grove 1996; Hope and others 2003; Martin and others 2004). The reason for this is that although lifestyle behavior was a better predictor of vegetation cover than social stratification, socioeconomic status is major data component of both of these PRIZM categorizations. Thus, it is reasonable to find that analyses using socioeconomic status would yield significant results. Our findings indicate, however, that including additional household characteristics associated with lifestyle behavior provide better results, at least for vegetation cover. This distinction is amplified by the fact that our preliminary analysis of space available for planting vegetation—parcel area minus building area—is predicted best by social stratification and not by lifestyle behavior (A. R. Troy and others, unpublished). Thus, social stratification is a better predictor of the possibility for vegetation, but lifestyle behavior is a better predictor of the vegetation cover that is realized. Given that most of the previous research has focused on species composition, diversity, and abundance, this point needs to be examined further.

The results including median housing age showed that it was important to add a temporal component to the analyses. Median housing age is an increasingly important predictor of vegetation cover in private lands and PROWs until it reaches 40–50 years, when age declines as a predictor. The parabolic form of this result could help to reconcile the findings from Whitney and Adams (1980), Hope and others (2003) and Martin and others (2004) with observations from M. F. Galvin (personal communication) and Smith (2004). Most of the field samples of Hope and others (2003) and Martin and others (2004) were collected in areas where the median housing age was between 0 and 50 years (Figures 4.A.1 and 5.A.1), whereas Galvin and Smith studied areas where the median housing age was more than 40–50 years (Figures 4.B.2 and 5.B.2). The contrasting findings would be consistent with the quadratic form of the equation describing the significance of median housing age. Larger data sets stratified by median housing age and bracketing a potential 40–50 inflexion point would need to be tested to determine whether this relationship exists for species composition, diversity, and abundance.

A second temporal component of this research is related to the issue of association versus cause and effect. Our research used data that were collected within a 2–3-year period; thus, we can only claim associations among these data. The addition of time-series data would enable us to examine cause-and-effect relationships, such as whether specific lifestyle groups locate in areas with particular combinations and amounts of vegetation cover, or whether specific lifestyle groups manage for and cultivate particular combinations and amounts of vegetation cover. We believe that this issue is probably more complex. It could be, for instance, that some lifestyle groups would be more likely to move, whereas other lifestyle groups would be more likely to cultivate. In other words, the direction of the cause-and-effect relationship between household characteristics and vegetation cover may not be the same direction, and it may not occur at the same rate for all lifestyle groups. To examine this question further, time-series data and household interviews would be necessary.

Management Implications

The results of our research indicate that lifestyle behavior is a significant predictor of vegetation cover on both private lands and PROWs. These findings suggest that there is potential for novel management approaches that would implement environmental marketing strategies. Urban foresters and environmental planners now acknowledge the need to develop support for and participation in their programs among diverse constituencies (Svendsen 2005; Grove and others, accepted J. M. Grove and others, 2006a, unpublished). Examples of these constituencies include homeowners, neighborhood associations, developers, and business groups. Urban foresters and environmental planners might develop marketing strategies whereby they "sell" greener neighborhoods to different neighborhood-based consumer markets, building on their desire for social status and group identity. Indeed, Robbins and Sharp (2003) have described recent trends in how the manufacturers of lawn-care chemicals market their products to various consumer group by associating "community, family, and environmental health with intensive turf-grass aesthetics" and fostering household demand for "authentic experiences of community, family, and connection to the non-human biological world through meaningful work." To promote the goals of urban foresters and environmental planners, an ecological marketing strategy could be developed systematically by using the tools of geodemography and cluster-based market segmentation. In this way, they could measure different lifestyle groups' preferences and motivations for various environmental behaviors and then devise communication strategies and management activities that would address those preferences and motivations in a spatially explicit context.

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